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"MODELLING OF COMPLEX CHAOTIC SIGNALS USING ARTIFICIAINTELLIGENCE"

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ABSTRACT

In this project we are considering different Chaotic signals and their results so that we can work on the best method. Here Chaos (Irregular motions) are used. Filtering has been invoked to reduce the obviously noisy character of the monthly sunspot numbers. However, here shown that straight for wardlinear filtering can also make a stochastic signal appear to below-dimensional, so one cannot eliminate the possibility that the sunspot numbers are the result of a stochastic process with a "noisily periodic" component. We are comparing numerational knowledge based techniques for forecasting has been proved highly successful in present time. The purpose of this paper is to examine the effects of several important neural network factors on model fitting and forecasting the behaviors.

KEYWORDS: Artificial Neural Network (ANN), Data, Prediction, Forecasting, Foreign Exchange Rate, Autoregressive Integrated Moving Average (ARIMA)

INTRODUCTION

We investigate the effectiveness of connectionist architectures for predicting the future behavior of nonlinear dynamical systems. We stress on real-world time series of limited record length. Examples are analyzed: sunspot series and chaotic data from a computational ecosystem is the benchmark. The problem of over fitting, particularly serious for short records of noisy data, is addressed both by using the statistical method of validation and by adding a complexity term to the cost function ("back-propagation with weight-elimination"). The dimension of the dynamics underlying the time series, its Liapunov coefficient, and its nonlinearity can be determined via the network. We also show superiority of radial basis functions for high-dimensional input spaces. As, since the ultimate goal is accuracy in the prediction, we find that sigmoid networks trained with the weight-elimination algorithm outperform traditional nonlinear statistical approaches. The Artificial Neural Networks have received increasing attention as decision-making tools.

Artificial Neural Network

The electronic models of ANN are based on neural structure of the brain. One is 'artificial neurons'. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. When the signals received are strong enough i. e. surpass a certain threshold, the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron

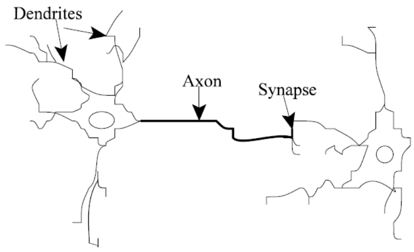

Figure 1: Natural Neurons (Artist's Conception)

Next function computes the output of the artificial neuron (in dependence of a certain threshold). For processing ANNs combine artificial.

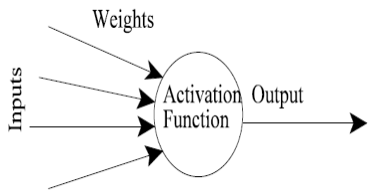

Figure 2: An Artificial Neuron

If the neuron have higher weight, the stronger the input which is multiplied by it will be. Negative weights are also there, then the signal is inhibited by the negative weight. Depending on the weights, the computation of the neuron will be different. We adjust the weights of an artificial neuron, we can obtain the output we want for specific inputs. But when we have an ANN of hundreds or thousands of neurons, it would be quite complicated to find by hand all the necessary weights. Using algorithms which can adjust the weights of the ANN in order to obtain the desired output from the network. Learning or training is this process of adjusting the weights.

Here we study behaviour and control in animals and machines, but also there are ANNs which are used for engineering purposes, such as pattern recognition, forecasting, signal processing and data compression.

LEARNING IN ARTIFICIAL NEURAL NETWORKS

Ability to learn is one of the most impressive features of artificial neural networks. And is the biological nervous system.

Learning Types

The different algorithms that can be used when training artificial neural networks, with their own specific advantages and disadvantages. The learning process within artificial neural networks is a result of altering the network's weights, with some kind of learning algorithm used there. The objective is to find a set of weight matrices involved there which when applied to the network should - hopefully - map any input to a correct output in last stage. Here we focus on supervised learning. But before we begin, lets take a quick look at the three major learning paradigms.

Supervised Learning

It is possible to calculate an error based on it's target output and actual output by providing the neural network with both an input and output pair. And the error is used to make corrections to the network by updating it's weights.

Unsupervised Learning

This type of learning is used by many recommendation algorithms because of their ability to predict a user's preferences based on the preferences of other similar users it has grouped together.

Reinforcement Learning

Reinforcement learning is similar to supervised learning, instead of providing a target output a reward is given based on how well the system performed in different conditions. It is trial-and-error process. This paradigm relates strongly with how learning works in nature.

ANN

Artificial neural networks (ANNs) and auto-regressive integrated moving average (ARIMA) models for time series forecasting are briefly reviewed.

The ANN Approach to Time Series Modeling

The network model is largely determined by the characteristicsof the data. Single hidden layer feed forward network is the most widely used model form for time series modeling and forecasting.

The Auto-Regressive Integrated Moving Average Models

Here the data transformation is often required to make the time series stationary. Stationarity is a necessary condition in building an ARIMA model used for forecasting. A stationary time series is characterized by statistical characteristics such as the mean and the autocorrelation structure being constant overtime. When the observed time series presents trend and heteroscedasticity, differencing and power transformation are applied to the data to remove the trend and to stabilize the variance before an ARIMA model can be fitted.

ARTIFICIAL NEURAL NETWORK FOR TIME SERIES FORECASTING

Issues in ANN Modeling for Forecasting

ANNs have many satisfactory characteristics, building a neural network forecaster for a particular forecasting problem is a nontrivial task. So the modeling should be done carefully. One critical decision is to determine the appropriate architecture, that is, the number of layers, the number of nodes in each layer, and the number of arcs which interconnect with the nodes. Different network design decisions include the selection of activation functions of the hidden and output nodes, the training algorithm, data transformation or normalization methods, training and test sets, and performance measures.

Proposed Design Comparison

From [1] The number of hidden nodes allows neural networks to capture nonlinear patterns and detect complex relationships in the data. We experiment with a relatively large number of input nodes. There is no upper limit on the possible number of hidden nodes in theory. However, it is rarely seen in the literature that the number of hidden nodes is more than doubling the number of input nodes. The combination of ten input nodes and five hidden nodes yields a total of 50 neural network architectures being considered for each insample training data set. A comprehensive study of neural network time series forecasting, finds that neural network models do not necessarily require large data set to perform well. Three-layer feed forward neural networks are used to forecast the Indian Rupee (INR) / US Dollar (USD) exchange rate.

Logistic activation functions are employed in the hidden layer and the linear activation function is utilized in the output layer.

From [2] Data Sets: The basic data set is the monthly mean Wolf sunspot numbers, hereinafter referred to as the “raw” sunspot numbers. The analytical methods are data intensive, forcing us to use all values. From the raw sunspot numbers, we can construct a number of other data sets. First, one makes the smoothed monthly sunspot numbers via a centered 12-month averagewe refer to this set as the “smoothed”sunspot numbers. Consequently, we make the “unrectified” sunspot numberset by (essentially) alternating the signs of the sunspot numbers each solar cycle. The detailed process is as follows:first they find the minima of the smoothed monthly sunspot number set. Those minima become our first guess for thetimes where the sign of the sunspot numbers changes (theantirectification points). A trial unrectified set is made, andthat set is then smoothed via the same centered 12-monthaveraging process. The zero crossings of the smoothed setare the second guess for the antirectification points. A new trial unrectified set is made from the original raw sunspotnumber set; and this process is repeated until the set of antirectification points is stable (four iterations). Hence, on the basis of both thephysical magnetic reversals and the spectral evidence, we suggest that the unrectified sunspot number set is actually the fundamental data set. From the unrectified sunspot numbers, we make the “smoothed unrectified” sunspotnumbers via the centered 12-month average.

From [3] The exchange rates between the Indian Rupee (INR) / US Dollar (USD) are obtained from Datastream International. These papers examine the effects of several factors on the in sample fit and out of sample forecasting capabilities of neural networks. The neural network factors investigated are the number of inputs and hidden nodes which are two critical parameters in the design of a neural network. The number of input nodes is perhaps the most important factor in neural network analysis of a time series since it corresponds to the number of past lagged observations related to future values. It also plays a role in determining the autocorrelation structure of a time series. The number of hidden nodes allows neural networks to capturenonlinear patterns and detect complex relationships in the data. We experiment with a relatively large number of input nodes. There is no upper limit on thepossible number of hidden nodes in theory. However, it is rarely seen in the literature that the number of hidden nodes is more than doubling the number of input nodes. In addition, previous research indicates that the forecasting performance of neural networks is not as sensitive tothe number of hidden nodes as it is to the number of input nodes. Thus, five levels of hiddennodes, 6, 12, 18, 24 and 30 will be experimented.

The combination of ten input nodes and fivehidden nodes yields a total of 50 neural network architectures being considered for each insampletraining data set. A comprehensive study of neural network time series forecasting, findsthat neural network models do not necessarily require large data set to perform well. To testif there is a significant difference between large and small training samples in modeling andforecasting exchange rates, we use two training sample sizes in our study. The large sampleconsists of 1043 observations from 1989 to 2009 and the small one includes 365 data points from2003 to 2009. The test sample for both cases is the 2010 data which has 52 observations. The random walk model will be used as a benchmark for comparison. The random walk is a one-step aheadforecasting model since it uses the current observation to predict the next one Three-layer feed forward neural networks are used to forecast the Indian Rupee (INR) / US Dollar(USD) exchange rate. Logistic activation functions are employed in the hidden layer and the linear activation function is utilized in the output layer. We are interested in one-step-ahead forecasts, one output node are deployed in the output layer. The of using of direct optimization procedure in neural network training. To be more certain of getting the

true global optima, acommon practice is to solve the problem using a number of randomly generated initial solutions. We train each network 50 times by using 50 sets of different initial arc weights. The best solutionamong 50 runs is used as the optimal neural network training solution.

RESULTS

The plots between the desired output and actual neural network output are plotted for these three models for short-term (1, 6 and 12) and long-term (18 and 24) months ahead prediction on testing data set. By the close visual inspection of the plots shown in Figure. 3a for FTLRNN model, Figure. 3b for MLPNN and Figure.3c for SOFMNN model for 1-month ahead prediction, the focussed time lagged recurrent neural network (FTLRNN) model closely follows the actual output as compared to the static MLPNN and SOFMNN model.

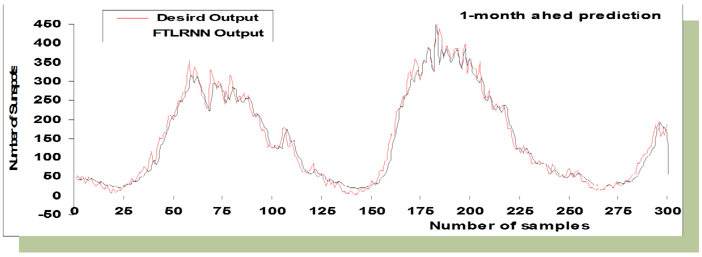

Figure 3: a Desired and FTLRNN Outputs for 1-Month Ahead Prediction

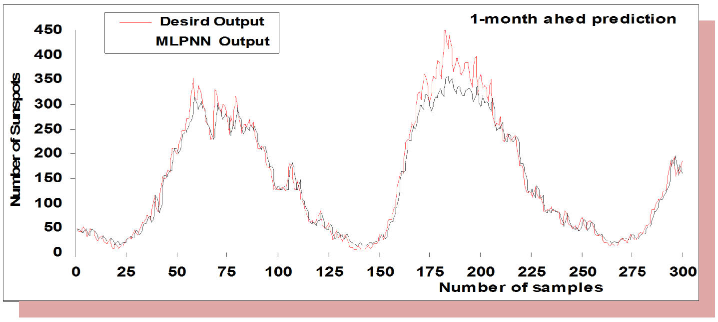

Figure 3: b Desired and MLPNN Outputs for 1-Month Ahead Prediction

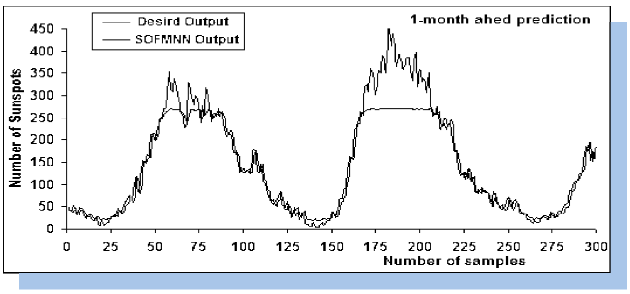

Figure.3: c Desired and SOFMNN Outputs for 1-Month Ahead Prediction

Similarly, the plot between desired output and actual neural network output are plotted for 6-month ahead prediction shown in Figure 4a for FTLRNN, Figure 4b for MLPNN model and Figure 4c for SOFMNN model. By close visual inspection of the Figure 4a, the FTLRNN predictor closely follows the desired output. The MLPNN and SOFMNN are failed to follow the desired output well as seen from the plot Figure 5b and Figure. 5c.

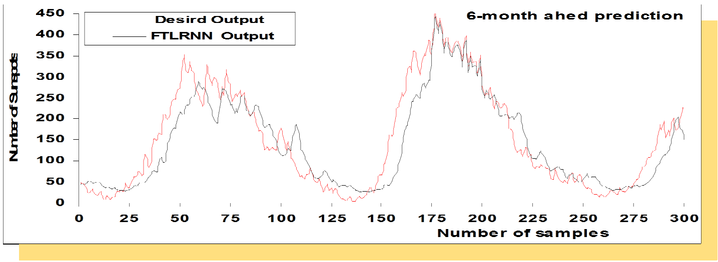

Figure 4: a. Desired and FTLRNN Outputs for 6-Month Ahead Prediction

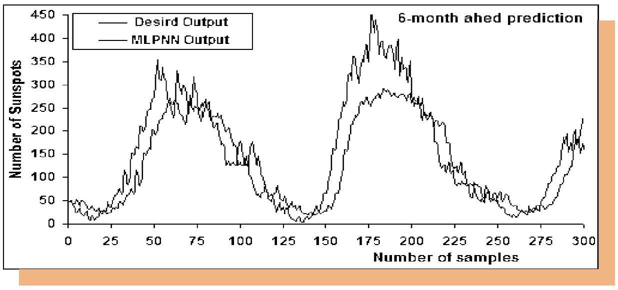

Figure 4: b Desired and MLPNN Outputs for 6-Month Ahead Prediction

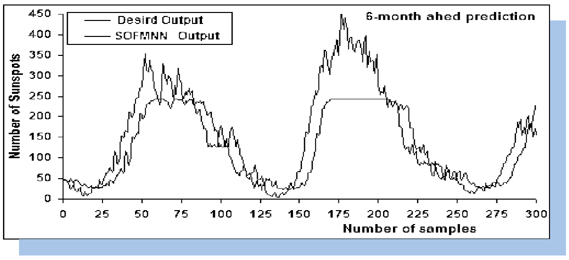

Figure 4: c Desired and SOFMNN Outputs for 6-Month Ahead Prediction

Then for 12-month ahead prediction, the plot between desired and actual output are plotted as demonstrated in Figure 5a for FTLRNN, Figure 5b for MLPNN and Figure 5c for SOFMNN predictor. It should be noted that the FTLRNN output is deviating slightly the desired output but far better than the MLPNN and SOFMNN.

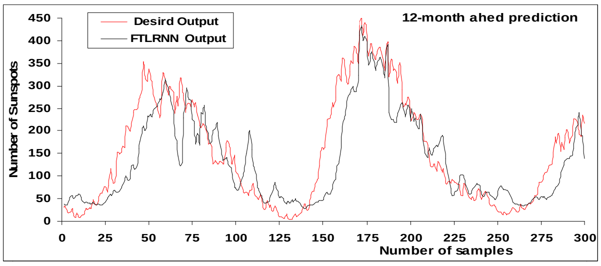

Figure 5: a Desired and FTLRNN Outputs for 12-Month Ahead Prediction

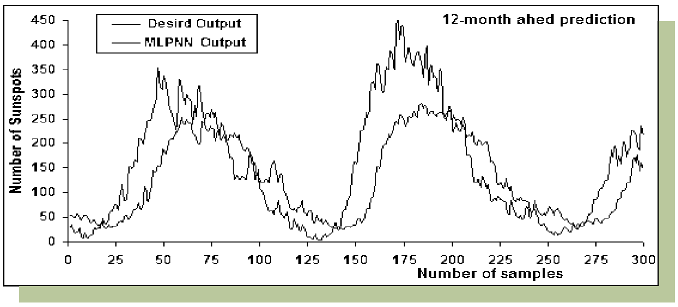

Figure 5: b Desired and MLPNN Outputs for 12-Month ahead Prediction

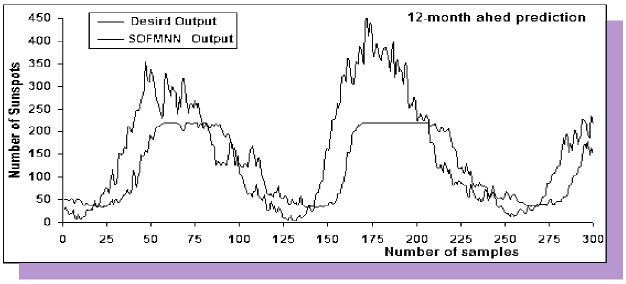

Figure 5: c Desired and SOFMNN Outputs for 12-Month Ahead Prediction

Next for 18-month ahead prediction the plot between desired output and actual output is shown in Fig.4a for FTLRNN, Fig. 4b for MLPNN and 4c for SOFMNN model. It is also noted that the output of FTLRNN predictor is deviating marginally from the desired output. The MLPNN and SOFMNN predictors failed to follow the desired output.

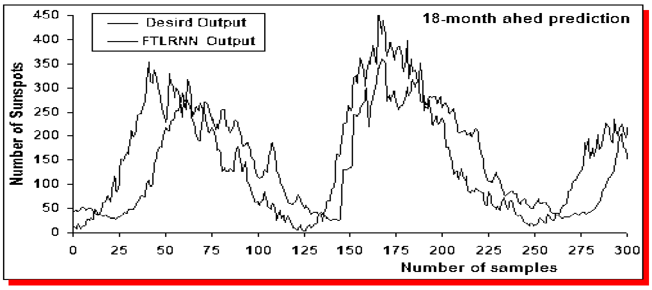

Figure 6: a Desired and FTLRNN Outputs for 18-Month Ahead Prediction

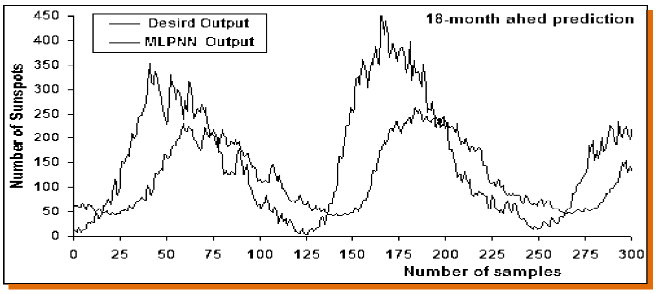

Figure 6: b Desired and MLPNN Outputs for 18-Month Ahead Prediction

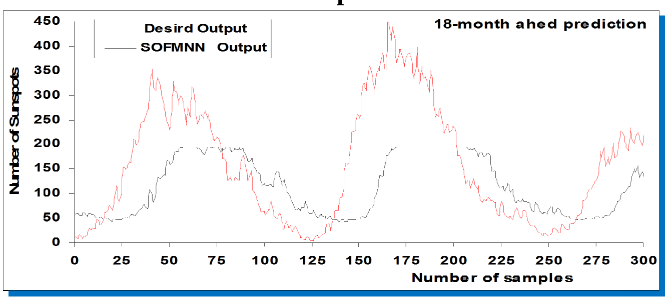

Figure 6: c Desired and SOFMNN Outputs for 18-Month Ahead Prediction

Similarly, for 24-month ahead prediction, the plot between desired output and actual output are plotted as illustrated in Fig.6a for FTLRNN predictor, in Fig.6b for MLPNN predictor and in Fig.6c for SOFMNN NN predictor. It is

clear that the FTLRNN output followed the desired output. The MLPNN and SOFMNN output failed to follow the desired output completely.

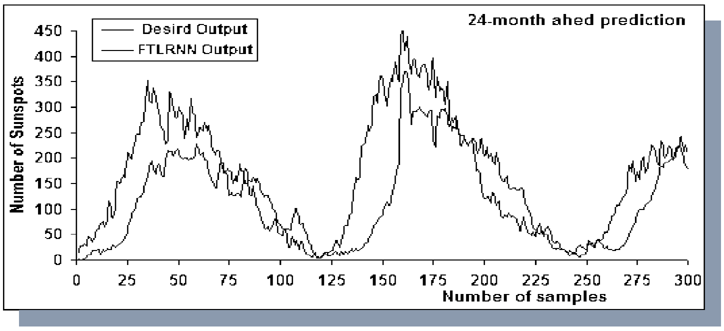

Figure 7: a Desired and FTLRNN Outputs for 24-Month Ahead Prediction

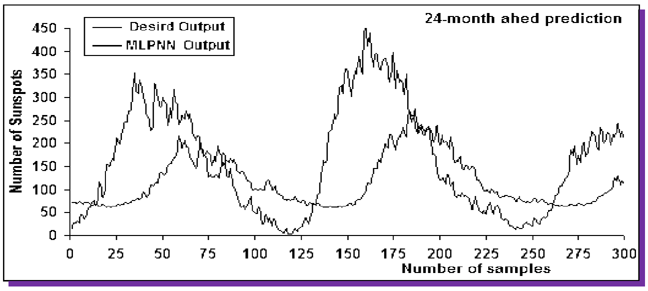

Figure 7: b Desired and MLPNN outputs for 24-month Ahead prediction

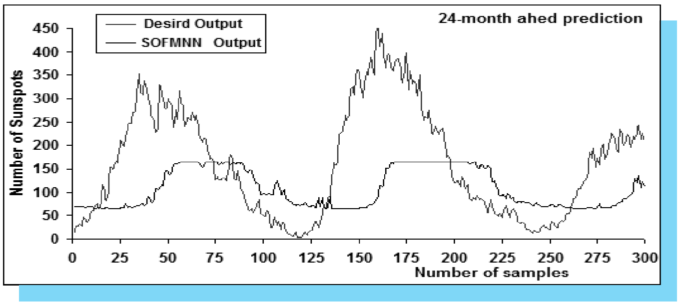

Figure 7: c Desired and SOFMNN Outputs for 24-Month Ahead Prediction

Thus FTLRNN model has learned the dynamics of the complex monthly sunspot chaotic time series elegantly well. On the contrary, the MLPNN and SOFMNN model failed to cope up with the underlying nonlinear dynamics for short-term (1, 6 and 12) and for long-term (18 and 24) month ahead prediction.

Table 1: 24-month ahead Prediction, Data Partitioning for FTLRNN

Data Partitioning		Testing Data Set		
Training	Testing	MSE	NMSE	*R*
10 %	75%	0.03246	0.37734	0.49224
20 %	65%	0.03657	0.58297	0.43616
30 %	55%	0.02280	0.52882	0.69373
40 %	45%	0.01839	0.83622	0.77659
50 %	35%	0.04066	0.41935	0.53973

60 %	25%	0.03059	0.54899	0.71497
70 %	15%	0.02834	0.95150	0.75528
80 %	05%	0.02339	0.57734	0.8012

CONCLUSIONS

It is seen that focused time lagged recurrent neural network model with gamma memory is able to predict the northern sunspots chaotic time series quite well in comparison with the Multilayer preceptron (MLP) and self organizing feature map (SOFM). Static NN configuration such as MLP NN based model and self organizing feature map (SOFM) network are failed to cope up with the underlying nonlinear dynamics of the sunspots chaotic time series. It is seen that MSE, NMSE of the proposed focused time lagged recurrent neural network (FTLRNN) dynamic model for testing data set as well as for training data set are significant better than those of static MLP NN and SOFMNN model. For the 12, 18 and 24 months ahead prediction the value of MSE and NMSE for the proposed FTLRNN model is significantly improved. Also for the proposed FTLRNN model the output closely follows the desired output for all the months ahead prediction for northern sunspots time series as shown in figures as compared to the MLP and SOFM. In addition it is also observed that the correlation coefficient of this model for testing and training are much higher than MLP and self organizing feature map (SOFM) neural network.

Applications of Anns as Forecasting Tools

To improve accuracy here we use the data to disciplines and the literature on forecasting using illustrate a method done to date in the area. In this section, There is an extensive literature of research activities in forecasting with cautions of ANNs. ANNs have find applications. Then we will discuss the research been used for forecasting bankruptcy and business methodology used in the literature.

FUTURE SCOPE

It is resulted from the experiments that the FTLRNN model learns thedynamics of northern monthly sunspot chaotic time series quite well as compared to Multilayer perceptron and self organizing feature map. On the contrary, it is observed that static MLP NN and self organizing feature map (SOFM) performs poorly bad, because on the one hand it yields much higher MSE and NMSE on testing data sets and on the other hand the correlation coefficient *r* for testing data set is far less than unity. This is also confirmed from the desired output Vs actual output plots for all the steps for MLP and SOFM model as shown in all figures are the months ahead prediction. Hence the focused time lagged recurrent neural network with gamma memory filter has out performed the static MLP based neural network and SOFM better for all the months' ahead predictions for monthly the chaotic time series.

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